Ecological Modelling 396 (2019) 33–41

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Modeling soil organic carbon dynamics under shifting cultivation and forests using Rothc model

Gaurav Mishra[a,*], Abhishek Jangir[b], Rosa Francaviglia[c]

[a] Rain Forest Research Institute, Jorhat, Assam, India
[b] National Bureau of Soil Survey & Land Use Planning, Nagpur, India
[c] CREA, Council for Agricultural Research and Economics, Research Centre for Agriculture and Environment, 00184, Rome, Italy

ARTICLE INFO

Keywords:
Climate change
Forests
Jhum land
North Eastern Himalaya of India
RothC
Soil organic carbon

ABSTRACT

Shifting cultivation (jhum) and forest land are the main land uses in North Eastern region of Indian Himalaya, but in the long term this form of agriculture is not acceptable due to the soil degradation following the cutting of forest vegetation, and the consequent biodiversity loss, high erosion rates and nutrient loss through runoff. No information on soil organic carbon (SOC) dynamics and simulation studies are available, so an attempt was done using RothC model. The model was parameterized on measured SOC contents of forest and jhum sites, and average SOC stocks and changes were simulated for a period of 5 years in forest and jhum sites under the baseline and the projected climate change conditions available for Nagaland state (2021–2050). Forest sites under the baseline climate showed a steady-state condition, and simulated SOC decreased by 0.04 t C ha^{-1} yr^{-1}during 5 years. In addition simulations indicated that forest land use could not benefit from climate change in a 10 years period (SOC changes showed a decreasing trend from 0.36 to 0.06 t C ha^{-1} yr^{-1}). Jhum sites showed negative changes in SOC stocks both under the baseline (0.40 t C ha^{-1} yr^{-1}) and the projected climate change conditions (0.50 t C ha^{-1} yr^{-1}). Indeed, SOC decreases under climate change were inversely related to the duration of the jhum cropping cycle, almost linear in the first five years (from 0.65 to 0.41 t C ha^{-1} yr^{-1}), and thereafter only slightly decreasing (from 0.39 to 0.32 t C ha^{-1} yr^{-1}). We can conclude that under climate change conditions the jhum cropping cycle can be extended for a longer period without substantial effects on SOC decreases.

1. Introduction

Forests are one of the most important ecosystems of the earth due to their biodiversity, ecosystems services and capacity to offset climate change impact through carbon sequestration (Basu, 2009; Rahman et al., 2017). However, due to anthropogenic pressure many of the forests are under stress (Brandon, 2014). Conversion of forest land to agricultural land by slash and burn is known as “shifting cultivation”, and is locally called *jhum* cultivation (Singh et al., 2014), a common practice in Africa, Asia and Latin America and this contributes to 70, 50 and 16% of total deforestation, respectively (FAO, 1957; Inoue et al., 2010; Chaplot et al., 2010; van Vliet et al., 2012; Grogan et al., 2012). *Jhum* cultivation is an ancient practice which consists of repetitive cycles: cutting the forest vegetation, leaving the biomass in situ to dry, burning the slashed vegetation after drying, and growing annual and perennial crops for a variable period of time, depending on the region. The ash deposits after burning, helps to fertilize the soil. After the end of the cycle the field is abandoned and the natural vegetation will grow (secondary forest), while the farmer (*jhumia*) will move to another site.

Due to geographical position and biodiversity richness, the North Eastern region of Indian Himalaya (NEH) is considered as one of the twelve biodiversity hot spots in the world (Choudhury et al., 2016). It is covered by forests (65%), agricultural land (16%) and fallow for the rest (Saha et al., 2012). Approximately 86% of the total cultivated area of NEH is under the practice of *jhum* cultivation and also is the major source of livelihood for the local peoples (Patel et al., 2013; Yadav, 2013). However, during the last few decades, this practice has led to rapid change in land use, especially in Nagaland (Chase and Singh, 2014). Continuous *jhumming* and changes in land use has also aggravated the issues related to soil degradation, biodiversity loss, and climate change (Salehi et al., 2008; Chase and Singh, 2014).

A wide number of studies have been done throughout the world, using different models and land uses, to understand the soil carbon dynamics at different temporal scales. Campbell and Paustian (2015)

* Corresponding author.
E-mail address: gaurav.mishra215@gmail.com (G. Mishra).

https://doi.org/10.1016/j.ecolmodel.2019.01.016
Received 27 August 2018; Received in revised form 15 January 2019; Accepted 18 January 2019
Available online 01 February 2019
0304-3800/ © 2019 Elsevier B.V. All rights reserved.

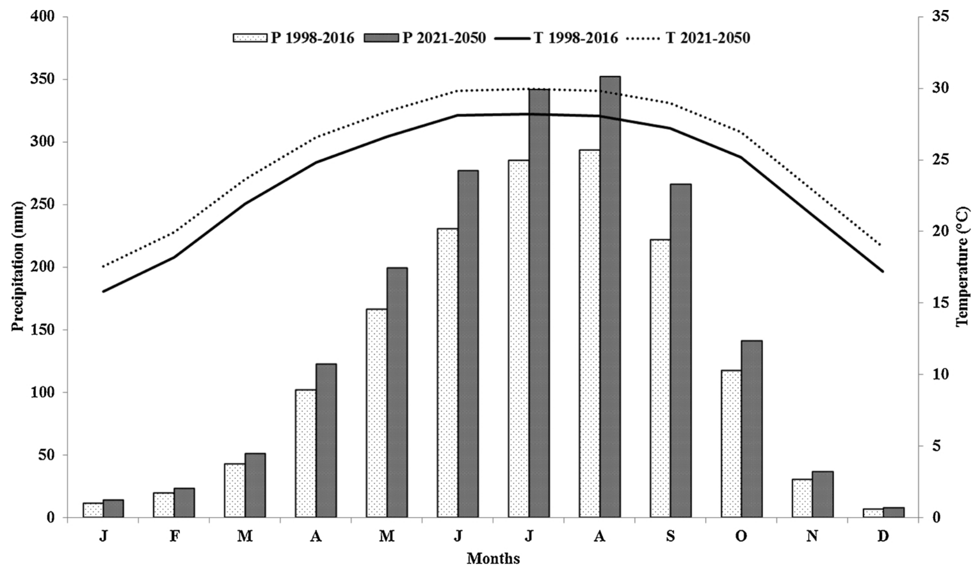


Fig. 1. Mean annual temperature (T) and precipitation (P) under the baseline climate (1998–2016) and climate change projections (2021–2050) for Dimapur and Kohima districts of Nagaland.

and Brilli et al. (2017) recently reviewed and discussed different simulation models available worldwide, commonly used for studies on SOC dynamics, GHGs emissions and climate change mitigation since simulated results provide information on the global carbon cycle, including the changes in SOC over time and soil carbon dioxide emissions. Models differ in the complexity and requirements of input information (Peltoniemi et al., 2007), and simple models need less complicated and less detailed input information than complex models. For example, RothC (Coleman and Jenkinson, 2014) requires only basic input data, whereas CENTURY (Parton et al., 1987) is more complex and the input data requirement is high. Both models have a similar structure, containing pools with rapid, moderate, and slow turnover.

RothC has been used in different countries and ecosystems including grassland, agriculture and forest in the UK and Iran (Coleman et al., 1997; Farzanmanesh et al., 2016); forests in Austria (Palosuo et al., 2012), Australia (Paul et al., 2003), Brazil (Cerri et al., 2007), Iran (Soleimani et al., 2017), Spain (Romanya et al., 2000) and Zambia (Kaonga and Coleman, 2008); olive groves in Spain (Nieto et al., 2010); land use and land use change in Italy (Francaviglia et al., 2012; Farina et al., 2017); arable crops in Australia (Senapati et al., 2014), China (Guo et al., 2007; Ludwig et al., 2010; Li et al., 2016), Germany (Ludwig et al., 2007) and Kenya (Kamoni et al., 2007).

Unfortunately, neither information related to SOC dynamics nor simulation studies are available for the North Eastern region of Indian Himalaya (NEH). Thus, we used the RothC model in this study to simulate the patterns of SOC stocks in two major land uses (forest and *jhum* lands) of this region, evaluate the response to future climate change projections, and provide better insights for climate change mitigation in the region as well as assistance in the management strategies in a long-term perspective.

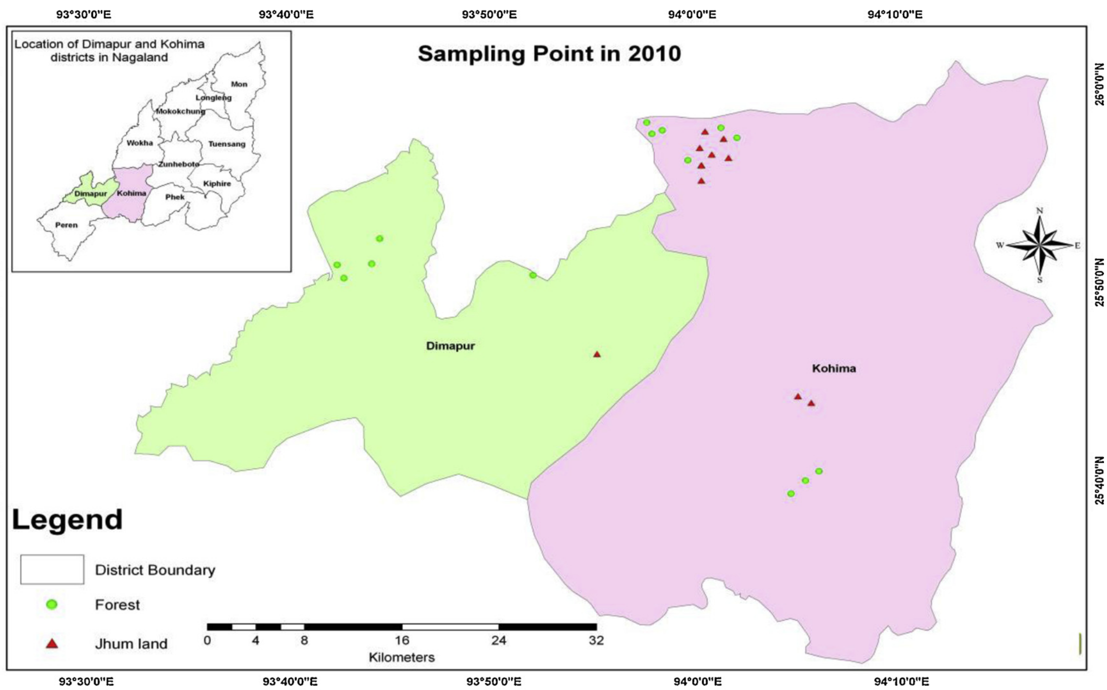
2. Materials and methods

2.1. Study area

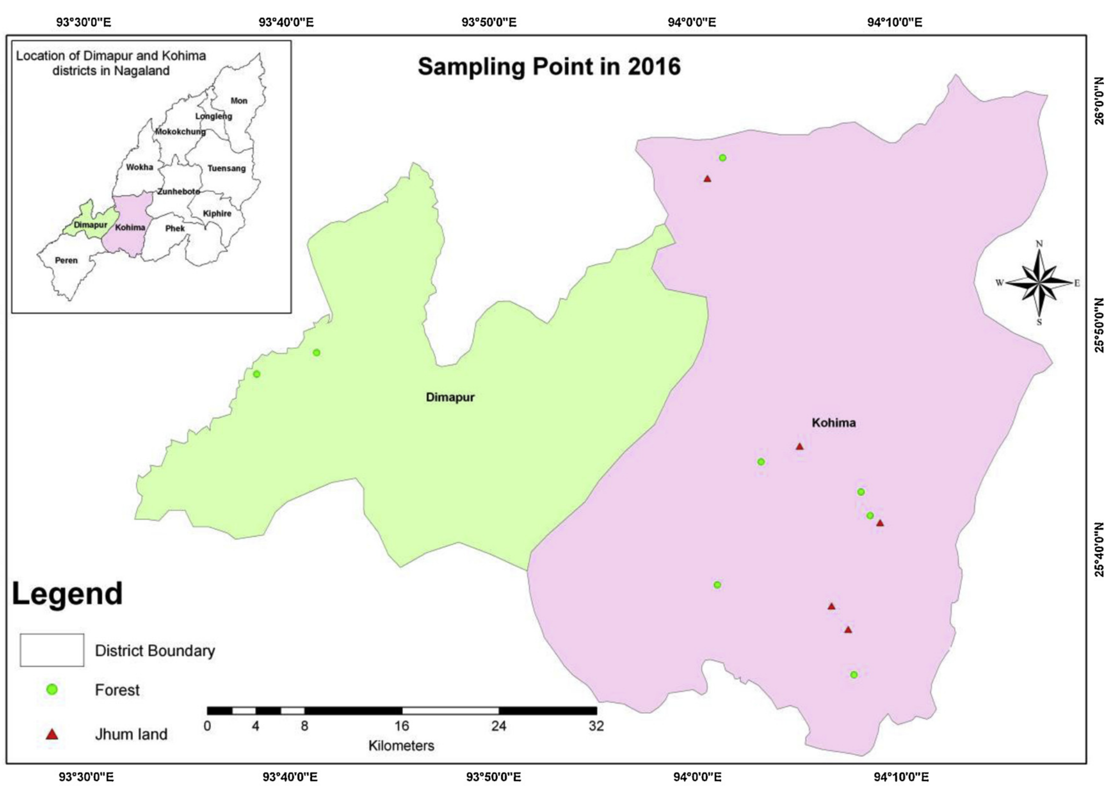
The study sites were located in Dimapur and Kohima districts of Nagaland state in the North Eastern region of Indian Himalaya (NEH). Nagaland borders the state of Assam to the west, Arunachal Pradesh and Assam to the north, Myanmar to the east, and Manipur to the south. Agriculture is the most important economic activity and other significant economic activity includes forestry, tourism, insurance, real estate, and miscellaneous cottage industries. The state is mostly mountainous except those areas bordering Assam valley which comprises 9% of the total area of the state. The two districts (Dimapur and Kohima), located at 25°06′–27°04′ N, 93°21′–95°15′ E, and 25°40′–25°67′ N, 94°07′–94°12′ E, occupy an area of about 927 and 1463 km^2, respectively. The altitude of Dimapur ranges from 260 to 690 above mean sea level, with temperature ranging from 20 to 25 °C and average annual rainfall of 1825 mm. Kohima lies in the elevation range from 690 to 1261 m above mean sea level. Kohima features a more moderate version of a humid subtropical climate (Cwa) with cool winters and hot rainy summers. During the height of summers, from June–August, temperature ranges an average of 27–32 °C. Average annual rainfall is 1831 mm, with 90% of it occurring during May to October. The majority of the forest areas in Kohima district are classified as tropical wet evergreen forest, and the major tree species of the selected forest sites (> 25 years old) were *Alnus nepalensis*, *Duabanga grandiflora*, *Gmelina arborea*, *Grevillea robusta*, *Melia azadirach*, *Pinus kesiya*. In Dimapur district, tree species belong mainly to *Alnus nepalensis*, *Bauhinia variegate*, *Ficus elastica*, *Gmelina arborea*, *Mesuaferrea*, *Pongamia* spp., *Tectona grandis*, *Terminalia bellerica*, *Schima wallichii*.

2.2. Climate and climate change projections

For baseline climate, the monthly values of average air temperature, precipitation, and open pan evaporation were obtained from the 19-year (1998–2016) data of the Indian Council of Agricultural Research (ICAR) Research Complex for the North Eastern region of Indian Himalaya in the state of Nagaland (25 45′24″N, 93 50′26″E, 295 m a.s.l.). Climate change projections to 2021–2050 were derived from the Nagaland State Action Plan on Climate Change (2012), based on PRECIS, a regional climate change model used for entire India including Nagaland. PRECIS down scales at 0.44° × 0.44° resolution (50 km^2) the outputs of the HadCM3 (Pope et al., 2000), a global climate model, whose outputs are at a resolution of 2.5° × 3.75° ˜ 280 km^2. Both PRECIS and HadCM3 have been developed by the Hadley CentreMet Office, UK, and the combination of HadCM3 and PRECIS models is known as the HadRM3 model. The pathways for atmospheric greenhouse gases (e.g. CO_2, CH_4, N_2O, CFCs) followed the IPCC SRES A1B mid-term (2021–2050) projections. District data have been derived by re-gridding the PRECIS model outputs at 0.2° × 0.2° resolution. Baseline and climate change projections for Dimapur and Kohima districts of Nagaland are shown in Fig. 1.



(a)



(b)

Fig. 2. Location of the sampling sites in 2010 (a) and 2016 (b) in Nagaland state.

2.3. Soil sampling and analysis

In 2010, a total of 26 sites were surveyed and soil samples (30 cm depth) were collected from forest (14) and jhum (12) lands (Fig. 2). Similarly, 13 soil samples were collected in 2016 from the same land uses (forest 8 and jhum 5). After sampling, the soil samples were stored in polyethylene bags, and subsequently processed prior to laboratory analysis. The samples were air-dried (at room temperature to constant

Table 1
Main soil parameters for the two land uses and sampling years. Data are referred to 30 cm (means ± SD).

Land use	Land use ID	Year	Bulk density (g cm^{-3})	pH	Silt (%)	Clay (%)	Sand (%)	SOC (%)	SOC (t C ha^{-1})
Forest1 (n = 14)	F1	2010	0.95 ± 0.10ab	5.12 ± 0.40 ns	21.35 ± 7.10ab	18.95 ± 5.80 ns	59.71 ± 10.85 ns	1.41 ± 0.89 ns	38.33 ± 18.87 ns
Jhum1 (n = 12)	J1	2010	0.92 ± 0.04a	5.04 ± 0.57 ns	16.74 ± 9.98a	21.85 ± 8.85 ns	61.50 ± 17.40 ns	1.20 ± 0.63 ns	32.74 ± 16.19 ns
Forest 2 (n = 8)	F2	2016	1.02 ± 0.13b	5.54 ± 0.69 ns	29.47 ± 7.52b	24.63 ± 12.18 ns	45.91 ± 14.25 ns	1.59 ± 0.60 ns	47.72 ± 17.42 ns
Jhum 2 (n = 5)	J2	2016	1.04 ± 0.05b	5.41 ± 0.38 ns	23.48 ± 8.21ab	22.48 ± 14.11 ns	54.04 ± 19.88 ns	1.19 ± 0.27 ns	36.99 ± 7.20 ns

SD standard deviation, SOC soil organic carbon. Different letters in each column indicate significant differences ($p < 0.05$) among samplings (Newman-Keuls test), ns not significant.

weight) and sieved through 2-mm sieve to exclude litter, roots and coarse particles. Particle size analysis was carried out by hydrometer method (Gee and Bauder, 1986) and bulk density (BD) by core method (Blake and Hartge, 1986). Soil organic carbon (SOC) was determined using $K_2Cr_2O_7$ wet oxidation method (Walkley and Black, 1934). Main soil characteristics are shown in Table 1. Soil organic C stocks were calculated with the formula:

$$SOC = C\ (\%) \times BD \times D \quad (1)$$

where SOC indicates the soil organic carbon stock (t C ha^{-1}), C is the percentage of organic carbon content, BD is the bulk density (g cm^{-3}), and D is thickness (cm).

2.4. Description of RothC model

The RothC model simulates the long-term dynamics of soil organic carbon (SOC) and CO_2 emissions in topsoil, for different vegetation types including arable crops, grasslands and forests. The model has a monthly step, and requires a limited number of input data: monthly climate (temperature, precipitation and pan evaporation), soil clay content, soil cover information (whether the soil is bare or under vegetation cover, since decomposition is faster in bare soils), quantity and quality of returned plant residues to soil, and farmyard manure inputs (FYM) if any (Coleman and Jenkinson, 2014).

SOC dynamics is simulated using four active compartments, i.e. decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), and humified organic matter (HUM), and an inert organic matter (IOM) compartment which is resistant to decomposition and does not take part in C turnover (Coleman and Jenkinson, 2014). IOM (t C ha^{-1}) is calculated from SOC using the equation proposed by Falloon et al. (1998):

$$IOM = 0.049 \times SOC^{1.139} \quad (2)$$

The model partitions the incoming quantity of plant residues into decomposable plant material (DPM) and resistant plant material (RPM), depending on the DPM/RPM ratio (quality of residues). DPM and RPM decompose to form CO_2, BIO and HUM in proportions based on the clay content. The BIO + HUM is then split into 46% BIO and 54% HUM, and both BIO and HUM decompose to form more CO_2, BIO and HUM (Fig. 3). In the present study, the RothC model version 26.3 (Coleman and Jenkinson, 2014) was used to simulate SOC dynamics.

The input data to run RothC simulations are included in two files. Land management file contains the monthly inputs of plant residues and farmyard manure in t C ha^{-1}, and the soil cover information (i.e. whether the soil is bare, 0 or covered, 1). Weather file includes the monthly values of temperature (°C), precipitation (mm) and pan evaporation (mm), besides clay content (%) and soil depth (cm).

2.5. Model parametrization

RothC-26.3 is designed to run in two modes: "forward" in which known carbon inputs are used to calculate the changes in soil organic matter and "inverse", when carbon inputs are calculated at equilibrium state for 10,000 years from known changes in soil organic matter.

Briefly, the model was firstly run at equilibrium in inverse mode, based on the known total soil carbon content, clay content, average climatic conditions and the presence of vegetation cover in the forest land use during the whole year. During this initialization process in inverse mode, the model automatically calculated the inert organic matter (IOM) from the known SOC content used as input, and iteratively calculated plant carbon inputs (to be included in the land management file) until the simulated SOC stock matched the measured SOC stock in the forest land use (Fig. 3). Thereafter, the model was run in the forward mode with a short term simulation for calibration in the jhum land use, considering the presence of vegetation cover for six months (May to December), and starting from the equilibrium conditions of forest land use. The new carbon inputs required to match as close as possible the measured SOC data of jhum sites in the calibration step were manually calculated (Fig. 3).

Residual quality factor (DPM/RPM ratio) was set to the default values for arable and woodland respectively, i.e. 1.44 for jhum and 0.25 for forests (Coleman and Jenkinson, 2014).Following the scheme reported in Table 2, two independent sets of simulations were run for the two sampling years (2010 and 2016), using the average measured SOC values and their standard deviation (SD) to provide a range of SOC stocks variations (Table 3).

First sampling 2010: the model was run at equilibrium (inverse mode) for forest F1 in 2010 (average climate 1998–2010), with the three measured SOC stocks (average, average + SD, and average – SD) and the C inputs iteratively calculated by the model. Then the management file was modified with a short term simulation (forward mode) for calibration on jhum J1 (average climate 2006–2010) to match the three SOC stocks (average, average + SD, and average – SD) measured in 2010 (calibration) and the C inputs were manually calculated. In detail, average SOC of jhum J1 was calibrated from average SOC of forest F1 at equilibrium, average + SD from average + SD of forest F1, and average – SD from average – SD of forest F1.

Second sampling 2016: the model was run at equilibrium (inverse mode) for forest F2 in 2016 (average climate 1998–2016), with the three measured SOC stocks (average, average + SD, and average – SD) and the C inputs iteratively calculated by the model. Then the management file was modified with a short term simulation (forward mode) for calibration on jhum J2 (average climate 2012–2016) to match the three SOC stocks (average, average + SD, and average – SD) measured in 2016 (calibration) and the C inputs were manually calculated. In detail, average SOC of jhum J2 was calibrated from average SOC of forest F2 at equilibrium, average + SD from average + SD of forest F2, and average – SD from average – SD of forest F2.

Shifting cultivations (jhum) consists of repetitive cycles with a variable period from 2 to 9 years (Maithani, 2005; Kumar et al., 2016a; Mishra et al., 2017), and 5 years can be considered an intermediate length. Therefore, SOC changes were simulated for a period of 5 years after the sampling using the equilibrium/calibration SOC stocks in forest and jhum sites respectively (Fig. 3), to derive the changes of SOC stocks in t C $ha^{-1}yr^{-1}$ for the two sampling periods under the baseline climatic conditions (Fig. 4a). For F1 and F2 forest sites (average and average ± SD), simulations were run with the same management files

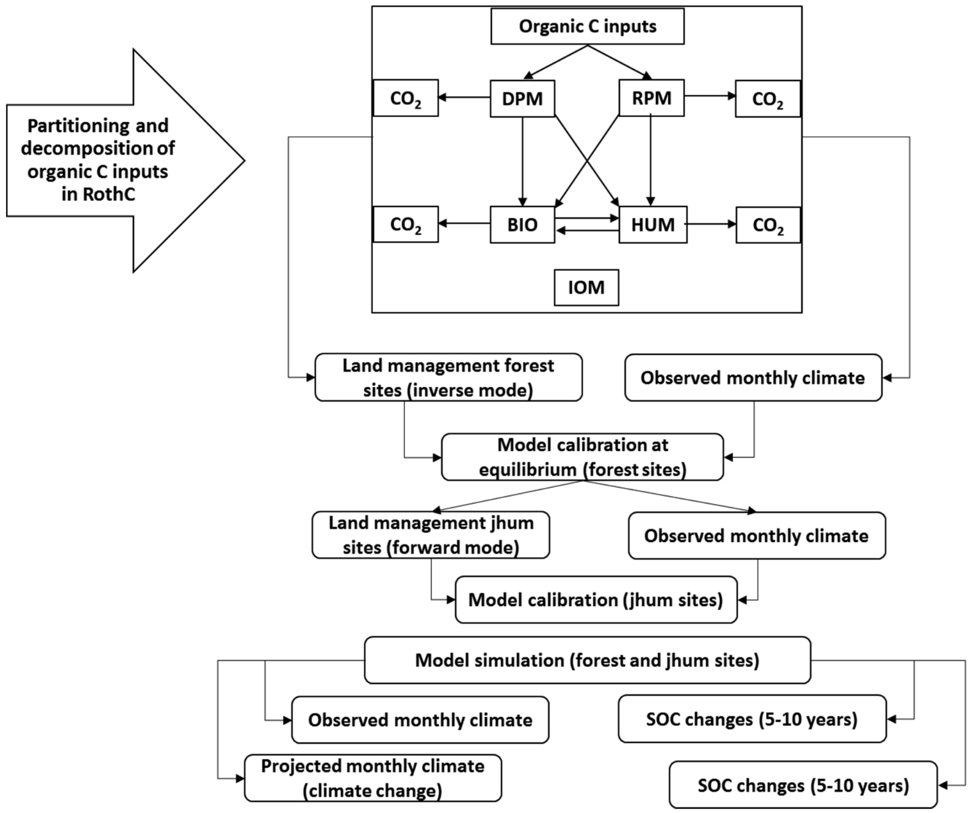


Fig. 3. Schematic conceptual model of the simulation procedure with RothC.

of equilibrium simulations, but using the yearly climates 2006–2010 and 2012–2016 respectively. For J1 and J2 jhum sites (average and average ± SD), simulations were run with the same management files of calibration simulations, but using the yearly climates 2006–2010 and 2012–2016 respectively. Analogously (Fig. 3), simulations were run for a period of 5 years to derive the average SOC stocks and changes for the two land uses and sampling periods under the projected climate change conditions (2021–2050) previously described (Fig. 4b).

A further set of simulations under climate change conditions was run for a period of 10 years, to provide information about SOC dynamics in a longer term for a possible extension of the jhum cropping cycle (Fig. 5). For jhum sites, simulated yearly and total SOC losses under climate change conditions were also calculated from year 1 to 5, and from year 6 to 10 of cultivation (Fig. 6). Total SOC losses were calculated considering the area of jhum fields (Bhalerao et al., 2015a,b) in the two districts of Dimapur (7800 ha) and Kohima (5420 ha).

2.6. Indicators of model performance

The overall agreement of model predictions with the measured values of SOC stocks in the jhum sites was tested using the correlation coefficient R^2, the root mean square error (RMSE) and the modeling efficiency (EF):

$$R^2 = \frac{\left(\sum_{i=1}^{n}(S_i - \bar{O})(O_i - \bar{O})\right)^2}{\sum_{i=1}^{n}(S_i - \bar{S})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{3}$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2\right]^{1/2} \tag{4}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{5}$$

where S_i and O_i are the i^{th} simulated and observed values respectively, $\bar{S}$ and $\bar{O}$ the average simulated and observed SOC values respectively, and n the total number of observations.

The lowest possible value of RMSE is zero, indicating that there is no difference between simulated and observed data. If the model accurately describes the measured data, RMSE should have approximately the same order of magnitude of the standard deviation (Smith and Smith, 2007). EF can range from -∞ to 1, with the best performance at EF = 1. Negative values indicate that simulated values do not describe the data as well as the mean of the observations.

Table 2
Clay content and soil organic carbon (SOC) for the two land uses and sampling years. Data are referred to 30 cm.

Land use	ID	Sampling year	Clay (%)	SOC (t C ha^{-1}) average	SOC (t C ha^{-1}) average + SD	SOC (t C ha^{-1}) average – SD
Forest 1	F1	2010	18.95	38.33	57.20	19.46
Jhum 1	J1	2010	21.85	32.74	48.93	16.55
Forest 2	F2	2016	24.63	47.72	65.14	30.30
Jhum 2	J2	2016	22.48	36.99	44.19	29.79

SD standard deviation, SOC soil organic carbon.

Table 3
Equilibrium (forest sites) and calibrated results (jhum sites) of model simulations.

Land use ID[a]	Avg. SOC (t C ha^{-1})		IOM[b] (t C ha^{-1})	C inputs (t C ha^{-1})	SOC + SD (t C ha^{-1})		IOM[b] (t C ha^{-1})	SOC – SD (t C ha^{-1})		IOM[b] (t C ha^{-1})
	Measured	Simulated			Measured	Simulated		Measured	Simulated	
F1[c]	38.33	38.33	3.12	5.47	57.20	57.20	4.92	19.46	19.46	1.44
J1[d]	32.74	32.74	–	6.60	48.93	48.67	–	16.55	16.86	–
F2[c]	47.72	47.72	4.00	6.72	65.14	65.14	5.70	30.30	30.30	2.39
J2[d]	36.99	37.01	–	5.04	44.19	44.32	–	29.79	29.52	–

[a] F1 forest sites 2010, J1 jhum sites 2010, F2 forest sites 2016, J2 jhum sites 2016, SOC soil organic carbon; SD standard deviation.
[b] IOM Inert Organic Matter.
[c] model run to equilibrium in "inverse mode".
[d] model calibrated after equilibrium from forest.

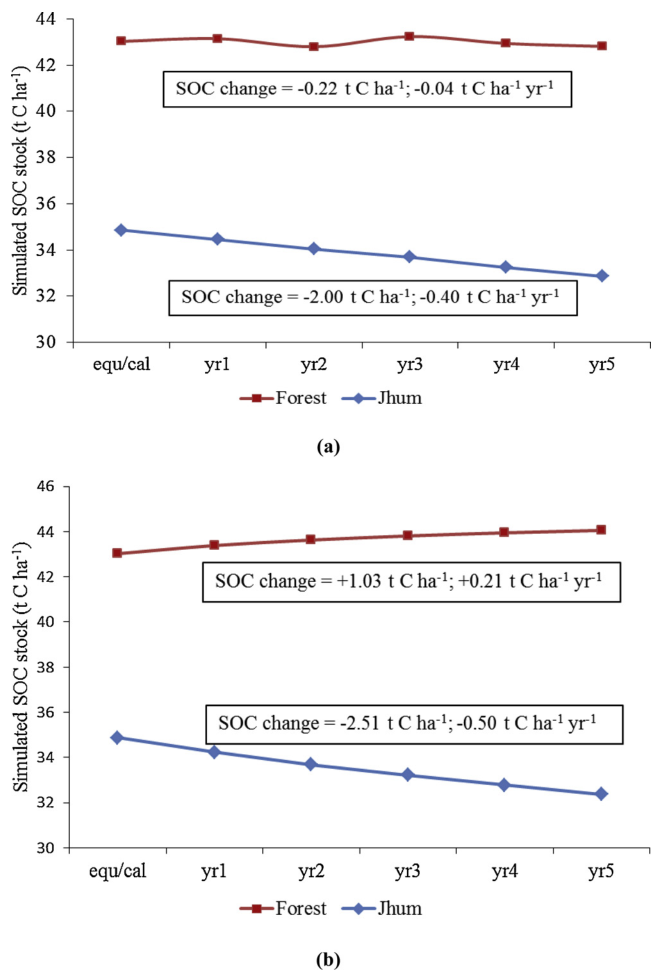


Fig. 4. Simulated SOC dynamics for forest and jhum sites during a five years period after equilibrium/calibration, under the baseline (a) and climate change conditions (b).

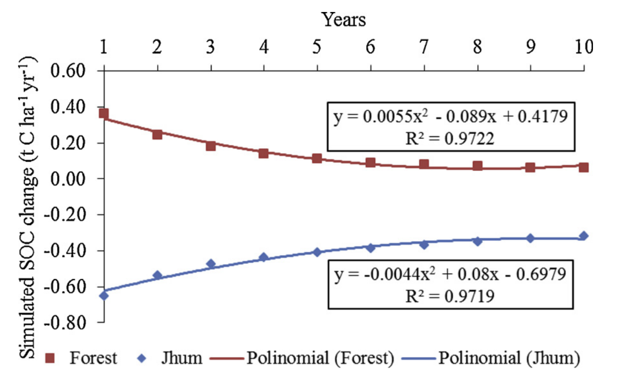


Fig. 5. Simulated SOC changes for forest and jhum sites during a ten years period under climate change conditions (2021–2050).

3. Results

3.1. Carbon stocks, carbon inputs and model results

Measured SOC stocks were lower in jhum land use (J1 and J2) compared with forest sites (F1 and F2) in both sampling years (Tables 1 and 2). In particular, average stocks were 32.7 and 38.3 t C ha^{-1} in jhum J1 and forest F1 respectively in 2010, 14.6% lower in jhum J1 (5.6 t C ha^{-1}). Considering the standard deviations, SOC was 14.5–14.8% lower in jhum J1 (-2.9 to -8.3 t C ha^{-1}). Average stocks in 2016 were 37.0 and 47.7 t C ha^{-1} in jhum J2 and forest F2 respectively, 22.5% lower in jhum J2 (10.7 t C ha^{-1}). Considering the standard deviations, SOC was 1.7–32.2% lower in jhum J2 (-0.5 to -21.0 t C ha^{-1}).

Average calculated carbon inputs (Table 3) were 5.5 and 6.7 t C ha^{-1} for forest sites (F1 and F2 respectively) at equilibrium, 6.6 t C ha^{-1} for jhum sites (J1) after calibration from forest F1, and 5.0 t C ha^{-1} for jhum sites (J2) after calibration from forest F2. However, measured C inputs for forest land uses in the region are very scarce, and no data exist for jhum cultivation. Thus, we assessed if C inputs calculated with RothC were consistent with observations available from other studies in forest sites. Rathore et al. (2010) indicated a litter yield of 13.56 t ha^{-1} for *Alnus* trees, that with a C content of 45% (Johnson et al., 2006) would provide a litter input of 6.10 t C t ha^{-1}. Gosain et al. (2015) reported a C input to forest floor through litter fall equal to 4.21 tC ha^{-1} for pine forests. Similarly, litter fall values in pine forests have been reported ranging from 4.2 to 6.5 tC ha^{-1} yr^{-1} by Singh and Singh (1992).Thus, researches are in good agreement with the C inputs calculated with RothC at equilibrium for forest sites (5.47 and 6.72 t C t ha^{-1} in F1 and F2 respectively). For jhum land use, we considered rice as main cultivation and estimated the annual C inputs by the formulas derived from Kong et al. (2005); Kuzyakov and Domanski (2000); Skjemstad et al. (2004), based on yields, harvest index (HI) and shoot:root ratio (S:R). Based on the field research carried out by Kumar et al. (2016b) according to the local farmers' practice, these rice parameters were 3.31 t ha^{-1}, 0.40 and 0.80 respectively. Total C inputs (Ctot) were calculated by the equation:

$$Ctot = Cs + Cr + Ce + Cw \tag{6}$$

were Cs, Cr, Ce and Cw are C from stubble, in roots, in root exudates, and weeds respectively. In detail:

$$Cs = 0.1 \times (Yield/HI) \times 0.45 \tag{7}$$

$$Cr = Yield/(HI \times S{:}R) \times 0.45 \tag{8}$$

$$Ce = 0.09 \times (Yield/HI) \times 0.45 \tag{9}$$

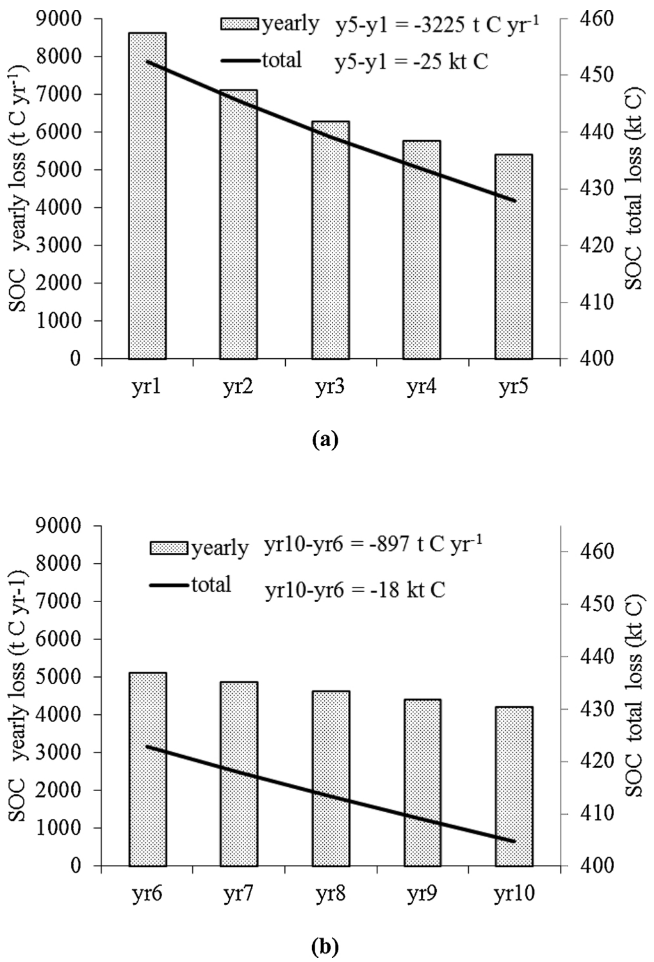


Fig. 6. Simulated yearly and total SOC losses for jhum sites under climate change conditions (2021–2050). Year 1–5 of cultivation (a), and year 6–10 (b).

$$Cw = 0.07 \times (\text{Yield/HI}) \times 0.45 \tag{10}$$

Applying Eq. (6) Ctot was 5.62 t C t ha^{-1}, in good agreement with the average value of jhum sites obtained by the calibration of RothC (5.82 t C t ha^{-1}).

3.2. Model validation

Following the equilibrium simulations in the forest sites, we simulated the conversion to jhum land-use and RothC results were validated using the three indicators of model performance previously described (see Materials and methods section). The agreement between measured and simulated data was quite good, since R^2, RMSE and EF were 0.989, 0.029, and 0.999 respectively, and the standard deviation of the measured values was also higher than RMSE with a value of 11.45. Based on these results, we can affirm that RothC predictions are fully acceptable for the purpose of this modeling exercise and can be used to simulate SOC stock changes under the baseline and climate change conditions as described in the following section.

3.3. Simulated carbon stock changes

Under the baseline climatic conditions and compared to the equilibrium simulated values for forest sites (Fig. 4a), average SOC stocks during the five years of simulation after samplings decreased by 0.22 t C ha^{-1}, and the yearly change was -0.04 t C ha^{-1} yr^{-1}. When compared to the calibrated values for jhum sites, average SOC stocks for jhum land use in the same period decreased by 2.00 t C ha^{-1}, and the yearly change was -0.40 t C ha^{-1} yr^{-1}(Fig. 4a).

The analogous simulations results under the projected climate change projections for a period of 5 years (Fig. 4b) showed an average SOC stocks change of 1.03 t C ha^{-1} in forest sites, and the average yearly change was 0.21 t C ha^{-1} yr^{-1}. Conversely, SOC stocks decreased by 2.51 t C ha^{-1} in jhum sites, with a yearly decrease equal to 0.50 t C ha^{-1} yr^{-1}as average.

Yearly SOC changes in forest and jhum sites during a period of 10 years under climate change conditions were interpolated by a polynomial equation (Fig. 5) to evaluate the effect on SOC stocks following a possible extension of the jhum cropping cycle for a longer time of period. Results indicated an average yearly SOC decrease in jhum sites equal to 0.43 t C ha^{-1} yr^{-1},lower than the average decrease during the 5 years simulation (0.50 t C ha^{-1} yr^{-1}). In detail, SOC decrease was inversely related to the duration of the cropping cycle, almost linear in the first five years (from 0.65 to 0.41 t C ha^{-1} yr^{-1}), and thereafter was only slightly decreasing (from 0.39 to 0.32 t C ha^{-1} yr^{-1}). At the same time, SOC change in forest sites was 0.14 t C ha^{-1} yr^{-1} as average, lower than the average change during the 5 years simulation (0.21 t C ha^{-1} yr^{-1}). Analogously to jhum sites, SOC change was almost linearly declining in the first five years in forest sites (from 0.36 to 0.11 t C ha^{-1} yr^{-1}), and thereafter was slightly declining (from 0.09 to 0.06 t C ha^{-1} yr^{-1}).

Considering the total area of jhum fields in Dimapur and Kohima districts (13,220 ha) yearly and total SOC loss during jhum cropping cycle were more pronounced from year 1 to 5 of cultivation and equal to 3225 t C yr^{-1} and 25 kt C respectively (Fig. 6a). From year 6 to 10 yearly SOC losses decreased to 897 t C yr^{-1}, and total SOC losses to 18 kt C (Fig. 6b).

4. Discussion

Forest sites under the baseline climate showed slightly negative SOC stocks changes, indicating a steady-state condition, and thus can be considered sustainable in the humid subtropical climate conditions of Dimapur and Kohima districts of Nagaland state. In addition, model simulations showed a decreasing trend of SOC stocks under the projected climate change conditions for forest sites, indicating that this land use could not benefit from climate change due to temperature and precipitation effects in a long term perspective, for example if simulations would be projected to longer periods (e.g. 30 years). In detail, SOC stocks would change by about 1.2 t C ha^{-1}during five years compared to the baseline conditions (1.03 vs -0.22 t C ha^{-1}), with a yearly change equal 0.25 t C ha^{-1} yr^{-1} (0.21 vs -0.04 t C ha^{-1} yr^{-1}). Jhum sites showed negative changes in SOC stocks during the five years of simulation both under the baseline and under the projected climate change conditions, but in the latter case the further decrease was equal to 0.51 t C ha^{-1} (2.00 vs 2.51 t C ha^{-1}), with an additional slight yearly decrease of 0.10 t C ha^{-1} yr^{-1}. For jhum sites, simulated yearly and total SOC losses were higher from year 1 to 5 (-37.4 and -5.4% respectively) compared to year 6 to 10 (-17.6 and -4.3% respectively), again showing that SOC decreases could be substantially higher when jhum cycle was shorter.

Beyond all inherent uncertainties in the use of simulation models, we did not know how many Jhum cycles took place after the shifting from forest in the selected sites before soil samplings. Other uncertainties could derive from climate change projections since in RothC SOC decomposition rates are governed by plant carbon inputs and are nonlinear functions of temperature and soil moisture patterns (Coleman and Jenkinson, 2014), thus climate has a primary influence on predicted soil carbon trends. In this study both temperature and precipitations increased under climate change, but Giorgi and Lionello (2008) indicated that precipitation projections are less robust than those of temperature since precipitation involves local processes of more considerable complexity than temperature. Nevertheless, the simulated effects on SOC dynamics are quite reasonable.

As already mentioned in the Introduction section, no simulation studies are available for SOC dynamics in shifting cultivation, thus we can only compare the measured SOC stocks with similar findings in the same area. Choudhury et al. (2016) studied SOC stocks in NEH region under different land uses, including shifting cultivation presently cultivated for different durations (2–8 years). Results were in good agreement with our findings and indicated a significant lower SOC stock in jhum (27.4 t C ha^{-1}) compared with the dense forest land use (35.2 t C ha^{-1}), but not significant in comparison with the open forest sites (30.1 t C ha^{-1}). Shifting cultivation showed about 22% less SOC stock than the dense forests, but only 9% less that the open forests. Mishra et al. (2017) assessed soil quality under shifting cultivation and forest sites in Wokha district of Nagaland (NEH), and average SOC stocks were 17.2% lower in jhum (46.9 t C ha^{-1}) than in forest sites (56.6 t C ha^{-1}).

According to Kumar et al. (2016a), the reduced cropping cycle is among the main constraints leading to a decline in the productivity and profitability of jhum fields mainly because of the population increase, and consequent increase in the demand for food. While the earlier cycle was 10–15 years, the present length is not enough to restore the functional capacity of soils after the initial forest clearing and burning in the early stages of plantations. In addition, shifting cultivation practices deteriorate soil fertility due to high soil losses by erosion, and a minimum period of 10–15 years would be essential to maintain the soil fertility for sustainable crop production. Anyhow, farmers harvest the crops by cutting or picking the economically important part, for instance paddy panicle or maize cob, leaving the crop residues on the slope of the hills which can help to protect the soil from erosion as well as enhance fertility after the decomposition (Kuotsuo et al., 2014). Kumar et al. (2016b) also reported that short jhum cycles (5 years) have lower fertility than those with longer cycles. Indeed, during the first year of jhum cultivation soil may have a better nutrient status, which can be lost in the following years due to leaching and runoff from sloping fields (Mishra et al., 2017).

Further constraints in jhum agriculture are water scarcity during the post-monsoon/winter seasons, lack of awareness about improved agriculture technologies and vegetable cultivation, and mono cropping with traditional practices and management. Different scientific interventions in soil, water and nutrient conservation, and crops can be undertaken to address these constraints (Kumar et al., 2016a): terracing of existing jhum land for wet rice-based farming systems, increasing of cropping intensity by introducing short-duration crops after rice fallow, introduction of high-yielding crops varieties and adoption of improved agro-techniques, restoration of degraded jhum lands through agroforestry-based farming systems, water-harvesting techniques for multiple purpose uses, and horticulture-based farming systems.

5. Conclusions

According to the Nagaland State Action Plan on Climate Change (2012), jhum land intensification and extension of cropping cycle is one of the key programs of research in agriculture, to be addressed by adopting improved farming practices and fallow management systems, so that productivity in jhum areas would increase.

In the present study, the RothC model was parameterized on measured SOC contents of forest and jhum sites, thereafter was used to simulate the dynamics of SOC under climate change conditions for a period of ten years, and results showed that the jhum cropping cycle can be extended for a longer period without substantial effects on SOC decreases. This target could be matched provided that jhum lands are properly managed, through cultivating the jhum for longer periods and managing the fallow period length. Conversion of further forests to jhum agriculture is not acceptable due to the soil degradation deriving from erosion and nutrient loss through runoff. For this reason, we recommend that further research in agriculture would be coupled with soil, water and nutrient conservation measures, as well as crop management practices, with the aim to store more C in soil and improve soil quality in jhum fields.

Acknowledgements

We greatly acknowledge the financial support from the Indian Council of Forestry Research and Education. We wish to thank the Forest Department of Nagaland for their support during the field visits and data collection. Last but not least, we thank all the staff of Rain Forest Research Institute, Jorhat, Assam, who have knowingly or unknowingly provided their help, support and cooperation in completing the study.

References

Basu, P., 2009. A green investment. If growing forest in India can generate lucrative carbon credits, then why isn't everyone planting trees? Nat. News 457 (7226), 144–146.
Bhalerao, A.K., Kumar, B., Singha, A.K., Jat, P.C., Bordoloi, R., Deka Bidyut, C., 2015a. Dimapur District Inventory of Agriculture. ICAR-Agricultural Technology Application Research Institute, Umiam, Meghalaya, India Accessed 19 December 2017. http://icarzcu3.gov.in/district_agri_inventory/Dimapur.pdf.
Bhalerao, A.K., Kumar, B., Singha, A.K., Jat, P.C., Bordoloi, R., Deka Bidyut, C., 2015b. Kohima District Inventory of Agriculture. ICAR-Agricultural Technology Application Research Institute, Umiam, Meghalaya, India Accessed 19 December 2017. http://icarzcu3.gov.in/district_agri_inventory/Kohima.pdf.
Blake, G.R., Hartge, K.H., 1986. Bulk density. In: Klute, A. (Ed.), Methods of Soil Analysis Part 1, Physical and Mineralogical Methods, 2nd edn. SSSA Book Series No.5. SSSA and ASA, Madison, Wisconsin, USA, pp. 951–984.
Brandon, K., 2014. Ecosystem Services from Tropical Forests: Review of Current Science. Working Paper 380. Center for Global Development, Washington, DC Accessed 19 December 2017. https://www.cgdev.org/publication/ecosystem-services-tropical-forests-review-current-science-working-paper-380.
Brilli, L., Bechini, L., Bindi, M., Carozzi, M., Cavalli, D., Conant, R., Dorich, C.D., Doro, L., Ehrhardt, F., Farina, R., Ferrise, R., Fitton, N., Francaviglia, R., Grace, P., Iocola, I., Klumpp, K., Léonard, J., Martin, R., Massad, R.S., Recous, S., Seddaiu, G., Sharp, J., Smith, P., Smith, W.N., Soussana, J.F., Bellocchi, G., 2017. Review and analysis of strengths and weaknesses of agro-ecosystem models for simulating C and N fluxes. Sci. Total Environ. 598, 445–470.
Campbell, E.E., Paustian, K., 2015. Current developments in soil organic matter modeling and the expansion of model applications: a review. Environ. Res. 10 (12), 123004.
Cerri, C.E.P., Easter, M., Paustian, K., Killian, K., Coleman, K., Bernoux, M., Falloon, P., Powlson, D.S., Batjes, N., Milne, E., Cerri, C.C., 2007. Simulating SOC changes in 11 land use change chrono sequences from the Brazilian Amazon with RothC and Century models. Agric. Ecosyst. Environ. 122, 46–57.
Chaplot, V., Bouahom, B., Valentin, C., 2010. Soil organic carbon stocks in Laos: spatial variations and controlling factors. Glob. Change Biol. Bioenergy 16 (4), 1380–1393.
Chase, P., Singh, O.P., 2014. Soil nutrients and fertility in three traditional land use systems of Khonoma, Nagaland, India. Resour. Environ. 4 (4), 181–189.
Choudhury, B.U., Fiyaz, A.R., Mohapatra, K.P., Ngachan, S., 2016. Impact of land uses, agrophysical variables and altitudinal gradient on soil organic carbon concentration of North Eastern Himalayan Region of India. Land Degrad. Dev. 27 (4), 1163–1174.
Coleman, K., Jenkinson, D.S., 2014. RothC — A Model for the Turnover of Carbon in Soil: Model Description and Users Guide (Updated June 2014). Lawes Agricultural Trust, Harpenden, UK Accessed 19 December 2017. https://www.rothamsted.ac.uk/sites/default/files/RothC_guide_WIN.pdf.
Coleman, K., Jenkinson, D.S., Crocker, G.J., Grace, P.R., Klir, J., Korschens, M., Poulton, P.R., Richter, D.D., 1997. Simulating trends in soil organic carbon in long-term experiments using the Verberne/MOTOR model. Geoderma 81, 29–44.
Falloon, P., Smith, P., Coleman, K., Marshall, S., 1998. Estimating the size of the inert organic matter pool from total soil organic carbon content for use in the Rothamsted carbon model. Soil Biol. Biochem. 30, 1207–1211.
FAO, 1957. Shifting cultivation. Unasylva 11 (1), 9–11.
Farina, R., Marchetti, A., Francaviglia, R., Napoli, R., Di Bene, C., 2017. Modeling regional soil C stocks and CO_2 emissions under Mediterranean cropping systems and soil types. Agric. Ecosyst. Environ. 238, 128–141.
Farzanmanesh, R., Abdullah, A.M., Latif, M.T., 2016. Modeling of soil organic carbon in the north and north-east of Iran under climate change scenarios. Sci. Iran. 23, 2023–2032.
Francaviglia, R., Coleman, K., Whitmore, A.P., Doro, L., Urracci, G., Rubino, M., Ledda, L., 2012. Changes in soil organic carbon and climate change – Application of the RothC model in agro-silvo-pastoral Mediterranean systems. Agric. Syst. 112, 48–54.
Gee, G.W., Bauder, J.W., 1986. Particle-size analysis. In: Klute, A. (Ed.), Methods of Soil Analysis Part 1, Physical and Mineralogical Methods, 2nd edn. SSSA Book Series No.5. SSSA and ASA, Madison, Wisconsin, USA, pp. 383–411.
Giorgi, F., Lionello, P., 2008. Climate change projections for the Mediterranean region. Glob. Planet. Change 63, 90–104.
Gosain, B.G., Negi, G.C.S., Dhyani, P.P., Bargali, S.S., Saxena, R., 2015. Ecosystem services of forests: carbon stock in vegetation and soil components in a watershed of Kumaun Himalaya, India. Int. J. Ecol. Environ. Sci. 41 (3-4), 177–188.
Grogan, P., Lalnunmawia, F., Tripathi, S.K., 2012. Shifting cultivation in steeply sloped

regions: a review of management options and research priorities for Mizoram state, Northeast India. Agrofor. Syst. 84 (2), 163–177.
Guo, L., Falloon, P., Coleman, K., Zhou, B., Li, Y., Lin, E., Zhang, F., 2007. Application of the RothC model to the results of long-term experiments on typical upland soils in northern China. Soil Use Manage. 23, 63–70.
Inoue, Y., Kiyono, Y., Asai, H., Ochiai, Y., Qi, J., Olioso, A., Shiraiwa, T., Horie, T., Saito, K., Dounagsavanh, L., 2010. Assessing land-use and carbon stock in slash-and-burn ecosystems in tropical mountain of Laos based on time-series satellite images. Int. J. Appl. Earth Obs. Geoinf. 12, 287–297.
Johnson, J.F., Allmaras, R.R., Reicosky, D.C., 2006. Estimating source carbon from crop residues, roots and rhizo deposits using the national grain-yield database. Agron. J. 98, 622–636.
Kamoni, P.T., Gicheru, P.T., Wokabi, S.M., Easter, M., Milne, E., Coleman, K., Falloon, P., Paustian, K., Killian, K., Kihanda, F.M., 2007. Evaluation of two soil carbon models using two Kenyan long term experimental datasets. Agric. Ecosyst. Environ. 122, 95–104.
Kaonga, M.L., Coleman, K., 2008. Modelling soil organic carbon turnover in improved fallows in eastern Zambia using the RothC-26.3 model. For. Ecol. Manage. 256, 1160–1166.
Kong, A.Y.Y., Six, J., Bryant, D.C., Denison, R.F., van Kessel, C., 2005. The relationship between carbon input, aggregation, and soil organic carbon stabilization in sustainable cropping systems. Soil Sci. Soc. Am. J. 69, 1078–1085.
Kumar, M., Kumar, R., Meena, K.L., Rajkhowa, D.J., Kumar, A., 2016a. Productivity enhancement of rice through crop establishment techniques for livelihood improvement in Eastern Himalayas. Oryza 53 (3), 300–308.
Kumar, R., Patra, M.K., Thirugnanavel, A., Chatterjee, D., Deka, B.C., 2016b. Towards the natural resource management for resilient shifting cultivation system in Eastern himalayas. In: Bisht, J.K., Meena, V.S., Mishra, P.K., Pattanayak, A. (Eds.), Conservation Agriculture. An Approach to Combat Climate Change in Indian Himalaya. Springer, Singapore, pp. 409–436.
Kuotsuo, R., Chatterjee, D., Deka, B.C., Kumar, R., Ao, M., Vikramjeet, K., 2014. Shifting cultivation: an 'Organic Like'Farming in Nagaland. Indian J. Hill Farm. 27, 23–28.
Kuzyakov, Y., Domanski, G., 2000. Carbon input by plants into the soil: review. J. Plant Nutr. Soil Sci. 163, 421–431.
Li, S., Li, J., Li, C., Huang, S., Li, X., Li, S., Ma, Y., 2016. Testing the RothC and DNDC models against long-term dynamics of soil organic carbon stock observed at cropping field soils in North China. Soil Till. Res. 163, 290–297.
Ludwig, B., Schulz, E., Rethemeyer, J., Merbach, I., Flessa, H., 2007. Predictive modelling of C dynamics in the long-term fertilization experiment at Bad Lauchstädt with the Rothamsted Carbon Model. Eur. J. Soil Sci. 58, 1155–1163.
Ludwig, B., Hu, K., Niu, L., Liu, X., 2010. Modelling the dynamics of organic carbon in fertilization and tillage experiments in the North China Plain using the Rothamsted Carbon Model-initialization and calculation of C inputs. Plant Soil 332, 193–206.
Maithani, B.P., 2005. Shifting Cultivation in North-east India: Policy, Issues and Options. Mittal Publications, New Delhi pp 163.
Mishra, G., Marzaioli, R., Giri, K., Borah, R., Dutta, A., Jayaraj, R.S.C., 2017. Soil quality assessment under shifting cultivation and forests in Northeastern Himalaya of India. Arch. Agron. Soil Sci. 63 (10), 1355–1368.
Nagaland State Action Plan on Climate Change, 2012. Achieving a Low Carbon Development Trajectory. Government of Nagaland, pp. 25–26. Accessed 19 December 2017. http://www.moef.nic.in/sites/default/files/sapcc/Nagaland.pdf.
Nieto, O.M., Castro, J., Fernández, E., Smith, P., 2010. Simulation of soil organic carbon stocks in a Mediterranean olive grove under different soil-management systems using the RothC model. Soil Use Manage. 26, 118–125.
Palosuo, T., Foereid, B., Svensson, M., Shurpali, N., Lehtonen, A., Herbst, M., Linkosalo, T., Ortiz, C., Todorovic, G.R., Marcinkonis, S., 2012. A multi-model comparison of soil carbon assessment of a coniferous forest stand. Environ. Model. Softw. 35, 38–49.
Parton, W.J., Schimel, D.S., Cole, C., Ojima, D., 1987. Analysis of factors controlling soil organic matter levels in Great Plains grasslands. Soil Sci. Soc. Am. J. 51 (5), 1173–1179.
Patel, T., Karmakar, S., Sanjog, J., Kumar, S., Chowdhury, A., 2013. Socio-economic and environmental changes with transition from shifting to settled cultivation in North-Eastern India: an ergonomics perspective. Int. J. Agric. Sci. Res. 3 (2), 117–136.
Paul, K.I., Polglase, P.J., Richards, G.P., 2003. Predicted change in soil carbon following afforestation or reforestation, and analysis of controlling factors by linking a C accounting model (CAMFor) to models of forest growth (3PG), litter decomposition (GENDEC) and soil C turnover (RothC). For. Ecol. Manage. 177, 485–501.
Peltoniemi, M., Heikkinen, J., Mäkipää, R., 2007. Stratification of regional sampling by model-predicted changes of carbon stocks in forested mineral soils. Silva Fenn. 41 (3), 527–539. Accessed 19 December 2017. http://www.metla.fi/silvafennica/full/sf41/sf413527.pdf.
Pope, V.D., Gallani, M.L., Rowntree, P.R., Stratton, R.A., 2000. The impact of new physical parametrizations in the Hadley Centre climate model: HadAM3. Clim. Dyn. 16, 123–146.
Rahman, M., Islam, M., Islam, R., Sobuj, N.A., 2017. Towards sustainability of tropical forests: implications for enhanced carbon stock and climate change mitigation. J. For. Environ. Sci. 33 (4), 292–299.
Rathore, S.S., Karunakaran, K., Prakash, B., 2010. Alder based farming system a traditional farming practices in Nagaland for amelioration of jhum land. Indian J. Tradit. Knowl. 9 (4), 677–680.
Romanya, J., Cortina, J., Falloon, P., Coleman, K., Smith, P., 2000. Modelling changes in soil organic matter after planting fast-growing Pinusradiata on Mediterranean agricultural soils. Eur. J. Soil Sci. 51, 627–641.
Saha, R., Chaudhary, R.S., Somasundaram, J., 2012. Soil health management under hill agroecosystem of North East India. Appl. Environ. Soil Sci. 2012, 1–9.
Salehi, A., Wilhelmsson, E., Soderberg, U., 2008. Land cover changes in a forested watershed, southern Zagros, Iran. Land Degrad. Dev. 19 (5), 542–553.
Senapati, N., Hulugalle, N.R., Smith, P., Wilson, B.R., Yeluripati, J.B., Daniel, H., Ghosh, S., Lockwood, P., 2014. Modelling soil organic carbon storage with RothC in irrigated Vertisols under cotton cropping systems in the sub-tropics. Soil Till. Res. 143, 38–49.
Singh, J.S., Singh, S.P., 1992. Forests of Himalaya: Structure, Functioning and Impact of Man. Gyanodaya Prakashan, Nainital, India, pp. 294.
Singh, A.K., Bordoloi, L.J., Kumar, M., Hazarika, S., Parmar, B., 2014. Land use impact on soil quality in eastern Himalayan region of India. Environ. Monit. Assess. 186, 2013–2024.
Skjemstad, J.O., Spouncer, L.R., Cowie, B., Swift, R.S., 2004. Calibration of the Rothamsted organic carbon turnover model (RothC ver. 26.3): using measurable soil organic carbon pools. Aust. J. Soil Res. 42, 79–88.
Smith, J., Smith, P., 2007. Introduction to Environmental Modelling. Oxford University Press, New York pp. 180.
Soleimani, A., Hosseini, S.M., Massah Bavani, A.R., Jafari, M., Francaviglia, R., 2017. Simulating soil organic carbon stock as affected by land cover change and climate change, Hyrcanian forests (northern Iran). Sci. Total Environ. 599-600, 1646–1657.
van Vliet, N., Mertz, O., Heinimann, A., Langanke, T., Pascual, U., Schmook, B., Adams, C., Schmidt-Vogt, D., Messerli, P., Leisz, S., 2012. Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: a global assessment. Glob. Environ. Change 22 (2), 418–429.
Walkley, A., Black, I.A., 1934. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci. 37, 29–38.
Yadav, P.K., 2013. Slash-and-burn agriculture in north-East India. Exp. Opin. Environ. Biol. 2, 1–4.